Hindawi
Mobile Information Systems
Volume 2022, Article ID 3381015, 11 pages
https://doi.org/10.1155/2022/3381015

Research Article

Forecasting Algorithm of Regional Economic Development Based on LPSVR

Yanxue Zhang[1] and Wei Cao[2]

[1]*College of Finance and Economics, Shanghai Lida University, Songjiang, 201620 Shanghai, China*
[2]*Business School, Xiamen Institute of Technology, Xiamen, 361021 Fujian, China*

Correspondence should be addressed to Wei Cao; 25620190154641@stu.xmu.edu.cn

Received 17 January 2022; Revised 23 February 2022; Accepted 4 March 2022; Published 7 April 2022

Academic Editor: Chia-Huei Wu

As an open and complex giant system, the development factors of regional economy restrict and promote each other and finally bring a high degree of nonlinearity to various data reflecting regional economic development. In addition, due to the difficulty of statistics, economic data has the characteristics of less data and large errors. This article is aimed at studying a regional economic development forecasting algorithm in order to change the traditional forecasting modeling technology that is increasingly difficult to meet the needs of regional economic development forecasting. The management department can analyze the results of the data mining model to improve the administrative management of the management department, later supervision ability, and work efficiency. In this article, a regional linear regression prediction algorithm based on linear regression is established to support regression vectors. In order to ensure the reliability of the prediction results, the concept of prediction reliability is introduced into the LPSVR algorithm and specific calculation methods are provided. At the same time, it shows that the LPSVR forecasting model outperforms the neural network algorithm in the research of regional economic forecasting. The experimental results of this paper show that the prediction accuracy of Guilin's annual GDP used by BP neural network is basically lower than that of LPSVR, which is 1.68%. LPSVR has shown good prediction performance in regional economic development prediction.

1. Introduction

1.1. Background. The economic system is a nonlinear and complex giant system. There are many factors that affect the direction of economic development, and these factors restrict each other, which make economic development have certain regularity, but at the same time, some of these influencing factors are difficult to obtain or even unknown to humans, which in turn gives economic forecasts brought great difficulties. Because business data has the characteristics of high data dimensions and autocorrelation between data, it is necessary to consider the autocorrelation of time series data in the process of regional economic trend forecasting and analysis, and it is necessary to reduce the impact of data autocorrelation on forecasting. In view of the abovementioned problems and the analysis of the problems, it is objectively urgent to apply effective data analysis techniques and methods to improve the decision-making analysis capabilities and data application effects of the business management system. Through the application and application of data analysis and visualization technology, this paper researches and designs a regional economic trend prediction and analysis system based on business data, assisting relevant leaders and staff of business management departments to further understand the relationship between regional market enterprise development and regional economic development, through data and technical support regional economic forecasts. BP neural network is relatively mature in terms of network theory and performance. Its outstanding advantages are its strong nonlinear mapping ability and flexible network structure. The number of intermediate layers of the network and the number of neurons in each layer can be arbitrarily set according to the specific situation, and its performance is also different with the difference of the structure.

1.2. Significance. From the perspective of data utilization, the data-based regional economic trend forecasting analysis system can provide a platform for data reuse and create data value. From the perspective of the regional economic trend forecasting analysis system, the construction of the system provides a set of analysis indicators from the three perspectives of market, industry, and enterprise, so that data analysis has a more complete analysis system. From the perspective of predictive analysis performance, the time series-based decision tree model in the system effectively solves the autocorrelation problem caused by the time series of the data, effectively reduces the classification forecast error rate, and better fits the market economic development trend. From the perspective of the administrative management of the management department, if the system is fully used in the system, the management department can analyze the results based on the data mining model, which improves the later supervision ability and work efficiency of the administrative department of the management department. From the perspective of the decision-making of the management department leaders, the system can assist the management department leaders to master the laws of economic development patterns, help the government correctly understand and understand the future direction of regional economic development, and make relevant decisions based on economic development trends. Provide an important reference basis for the government and related departments to optimize the industrial structure, evaluate, and formulate economic development policies. The traditional forecasting analysis method is difficult to obtain satisfactory results. Through the analysis of Guilin's annual statistical data, the LPSV forecasting model is used for empirical research.

1.3. Related Work. Regional partnerships are becoming more and more popular as mechanisms for solving public goods that transcend local boundaries, but we know little about their effectiveness. Chen et al.'s research found that with the emergence of regional partnerships, personal income, business companies, employment, etc., have all increased significantly [1]. Kasseeah proves that the development of coastal areas is better by studying the development of regional economy [2]. Zhao et al. used genetic algorithms to optimize the initial weights of the neural network to avoid local minima during neural network training [3]. It can be found that most of the relevant research focuses on the study of regional economic development, and there are not many studies on its prediction.

1.4. Innovation. The innovation of this article is as follows: (1) based on the introduction of statistical learning theory and SVM, a linear prediction model based on SVM is established, and the solution algorithm of the model and the general process of SVM regression prediction are given. (2) When optimizing the model, the grid search method is used to select the kernel function parameters and SVM parameters, and at the same time, the mutual influence relationship between the parameters is investigated, and finally, a set of parameters is selected to form the SVM with the most accurate combination of parameters. (3) Taking into account the timeliness characteristics of economic forecasting, the gray model suitable for small-sample forecasting is introduced into the model; at the same time, considering the limitations of the gray model such as being easily affected by random factors and poor long-term forecasting effects, the traditional partial gray model and the improved gray model based on the moving average are combined to construct a combined gray LPSVR model to predict future economic trends.

2. Linear Programming Support Vector Machine

2.1. Support Vector Regression SVR. Support vector regression SVR is a machine learning algorithm proposed on the basis of statistical learning theory in the late 1990s [4, 5]. For a given set of learning sample data,

$$Z = \{(x_i, y_i)\}, x_i \in R^n, y_i \in R, i = 1, 2, .., l. \tag{1}$$

The traditional regression learning method is to minimize the experience risk in order to obtain the relationship between input and output [6, 7]. Moreover, the statistical learning theory believes that in the case of limited samples, the smallest empirical risk cannot guarantee the smallest expected risk. Therefore, the structural risk minimization principle SRM is proposed, which is to minimize the experience risk and confidence range in the machine learning process [8, 9]. The SVR model based on SRM can be expressed as follows:

$$f(x) = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) K(x_i, x) + b. \tag{2}$$

In the formula, $K(x_i, x)$ is the kernel function. Commonly used kernel functions include polynomial kernel function, Gaussian radial basis kernel function, and multilayer perceptron kernel function [10, 11]. The parameters α_i and α_i^* in formula (2) are optimized by solving the equation:

$$\begin{aligned} \max\ W(\alpha, \alpha^*) = {} & \left[-\frac{1}{2} \sum_{i,j=1}^{l} (\alpha_i - \alpha_i^*) \left(\alpha_j - \alpha_j^* \right) K\left(x_i, x_j\right) \right] \\ & + \left[\sum_{i=1}^{l} (\alpha_i - \alpha_i^*) y_i - (\alpha_i + \alpha_i^*) \varepsilon \right], \end{aligned} \tag{3}$$

$$\text{S.t.} \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) = 0, \tag{4}$$

$$0 \le \alpha_i \alpha_i^* \le C,\ i = 1, \cdots, l. \tag{5}$$

The constant C in the constraint formula (5) is used to compromise the empirical risk and the confidence range. Under normal circumstances, most of the values of α_i and α_i^* are 0, and the samples corresponding to α_i or α_i^* values that are not 0 are called support vectors [12, 13]. Choose a support vector (x_i, y_i), the calculation formula of parameter

b in formula (2) is as follows:

$$b = y_j - \varepsilon - \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) y_i K(x_i, x_j), \tag{6}$$

$$b = y_j + \varepsilon - \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) y_i K(x_i, x_j). \tag{7}$$

Considering that the optimization formula (3) is a quadratic programming problem, when the sample data volume is large, the computational time and space complexity are both large [14]. Although the SVM time is long, it is within the receiving range. When the amount of data increases to 20,000 and the feature dimension increases to 200, the running time of SVM increases dramatically, far exceeding the running time of LR. But the accuracy is almost the same as LR.

2.2. Linear Programming Support Vector Machine Model. In fact, the optimization objective $W(a, at)$ of formula (3) consists of two parts, the first part is used to describe the confidence range, and the second part is used to measure the empirical error [15, 16]. The empirical error refers to the error obtained on the training set. Usually we call the ratio of the number of misclassified samples to the total number of samples as "error rate," the error of the learner on the training set is called "experience error" or "training error," and the error on new samples is called "generalization error." That is, the L2 norm is used to measure the confidence range, and the absolute value of the error is used to measure the empirical risk. In fact, there are other ways to measure the above two values, such as using the L1 norm to measure the confidence range. At this time, the corresponding SVR model is linear programming support vector regression (linear programming support vector regression, LPSVR) [16, 17]. It can be seen that, under the guidance of SRM, using linear programming to solve regression problems is to replace the standard risk function with the following risk function:

$$R_{\text{reg}}[f] = R_{\text{reg}}[f] + \gamma \sum_{i=1}^{l} |\alpha_i|. \tag{8}$$

In the formula, $R_{\text{emp}}(f)$ represents empirical risk through kernel function expansion, and LPSVR is available:

$$f(x) = \sum_{i=1}^{l} \alpha_i K(x_i, x) + b. \tag{9}$$

Since the absolute value sign in formula (8) is not easy to deal with directly, two parameters are used to solve it, and the ε-insensitive loss function is introduced at the same time; then, the LPSVR model can still be expressed by formula (2) [18, 19]. In the formula, the parameters and b are obtained by the following linear programming:

$$\min \sum_{i=1}^{l} (\alpha_i + \alpha_i^*) + C \sum_{i=1}^{l} (\beta_i + \beta_i^*), \tag{10}$$

$$\text{S.t.} y_i - \sum_{j=1}^{l} \left(\alpha_j - \alpha_j^*\right) K(x_i, x_j) - b \le \varepsilon + \beta_i, i = 1, \cdots, l, \tag{11}$$

$$\sum_{j=1}^{l} \left(\alpha_j - \alpha_j^*\right) K(x_i, x_j) + b - y_i \le \varepsilon + \beta_i^*, \text{i} = 1, \cdots, l, \tag{12}$$

$$\alpha_i, \alpha_i^*, \beta_i, \beta_i^* \ge 0, i = 1, \cdots, l. \tag{13}$$

The insensitive loss function can ignore the error of the true value within a certain upper and lower range, and its solution is characterized by the minimization of the function, which can ensure the sparsity of the dual variables, the existence of the global minimum solution, and the optimization of the reliable generalization bound. The slack variable is an auxiliary quantity in the support vector machine, which is used to convert the hard margin to the soft margin method, and its introduction can solve the impact of outliers on the classification. The value of the slack variable indicates how far the corresponding point is out of the group. The larger the value, the farther the point is. If the slack variable is zero, it means that the sample has no outliers. Obviously, the above optimization process is a linear programming problem, and the time and space required for calculation are obviously less than quadratic programming [20]. ε-insensitive loss function and slack variables are shown in Figure 1.

2.3. Predicting Trust. For pattern classification problems, a probability parameter is often given to describe the probability that the sample to be tested belongs to a certain category [21, 22]. However, when SVR is used for prediction, there is often only the output of the predicted value and no corresponding probability output [23]. The task of classification and discrimination must be oriented to a specific task or a specific cost. The purpose of classification is to reconstruct the internal model of the pattern we perceive and obtain a good pattern expression, which is a central task in almost all pattern recognition.

On the basis of the local prediction idea, a concept of prediction trust is defined in SVR, which is used to give a credibility measure of the prediction result [24, 25]. However, the acquisition of this value requires more sample data, so it cannot be applied to applications similar to economic forecasting. Here, the definition is expanded. The prediction error of the target subspace is calculated by using the local linear regression model, and the constraints of maximizing the dispersion between classes and minimizing the dispersion within the class are incorporated to define and solve the objective function, so as to obtain the optimal clustering subspace. Labeled and unlabeled samples are effectively utilized in this process.

For a given training sample set $Z = \{(x_i, x_j)\}$, $x_i \in R^n$,$y_i \in R$, $i = 1, 2, .., l$, suppose the regression function obtained according to the support vector regression algorithm is $f(x)$,

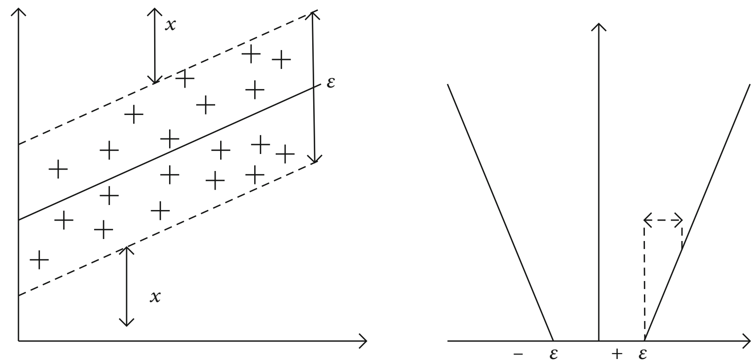

Figure 1: Insensitive loss function and slack variables.

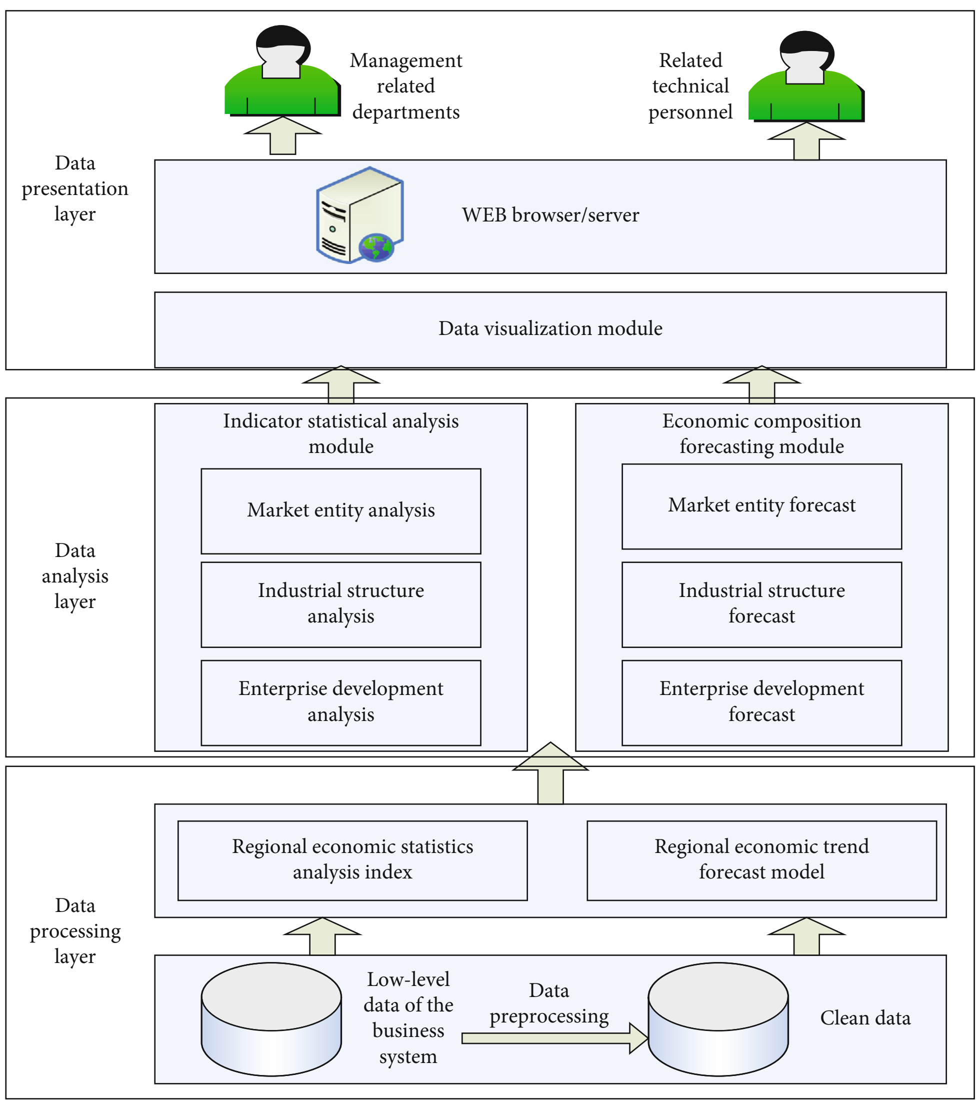

Figure 2: System architecture diagram.

Table 1: The error rate (MSE) of the economic forecast data set under the four models.

Model name	CPI	GDP
Traditional gray LPSVR	0.002002	0.004924
Unbiased gray LPSVR	0.001865	0.004385
Improving gray LPSVR by moving average method	0.001903	0.004215
Combination gray LPSVR	0.001898	0.004459

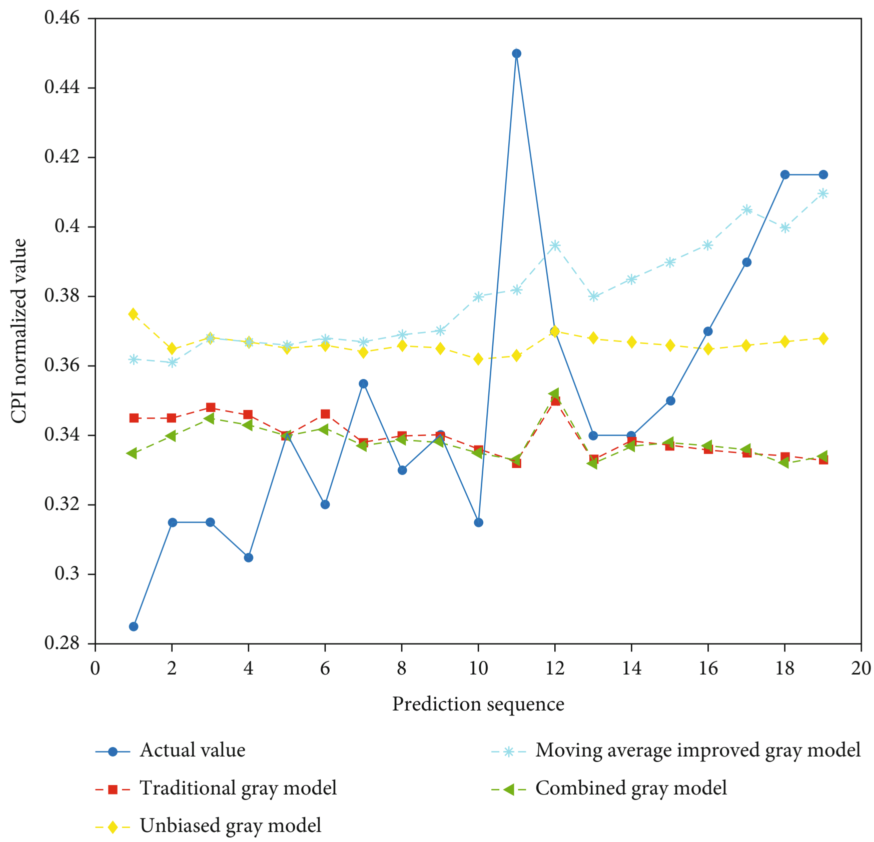

Figure 3: Comparison of CPI prediction results under multiple combination models.

then the prediction result of the new input x_{l+1} is $\widehat{y_{l+1}} = f(x_{l+1})$ [26]. Given the acceptable error $e > 0$, the e-prediction confidence of the predicted value $\widehat{y_{l+1}}$ is defined as follows:

$$PB_e\left(\widehat{y_{l+1}}\right) = \frac{\sum_{i=1}^{l} I(|y_i - f(x_i)| \leq e)}{l}. \quad (14)$$

With predictive trustworthiness, it also gives a preliminary concept of the trustworthiness of the predictive results.

3. Support Vector Machine Regression Prediction Model

The system architecture diagram is shown in Figure 2.

It can be seen from Figure 2 that this article divides the regional economic trend forecast and analysis system into two major modules. One is the business function module. The business module performs predictive analysis on the business and analyzes the related strategies. The second is the user module, based on a visual interface, to provide users with good decision support.

3.1. Traditional Economic Forecasting Models

3.1.1. Autoregressive Model (AR).

$$y_t = \mu + \sum_{i=1}^{p} \gamma_i y_{-t} + \varepsilon_i. \quad (15)$$

Among them, y_t represents the current value, μ is a constant term, ε_t is an error term, and $\sum_{i=1}^{p} \gamma_i y_{t-i}$ represents that the current value is related to the previous p order. AR can use statistics to calculate the correlation between the output variable and the value of the previous moment at different time lags. The stronger the correlation between the output variable and the specific lag variable, the greater the weight of the variable in the autoregressive model. Interestingly, if all the lagged variables have low or no correlation with the

Table 2: Original data.

Years	$X1$	$X2$	$X3$	$X4$	$X5$	$X6$
2015	6558116	34532	7199508	2024606	79025	99522
2016	8018228	42442	7823114	25 55530	73136	110248
2017	9956645	45034	8535962	3450674	70282	109119
2018	12693544	56654	9346711	3913564	100979	158509
2019	16219203	68214	10683290	4851221	176616	209119
2020	20063180	70423	12157584	6253516	177229	252054

Table 3: Correlation between GDP in year t and economic indicators in year $t-k$.

Index	Economic indicator data for $t-k$ years $K=1$	$K=2$	$K=3$
$X1$	0.1141	0.2176	0.0923
$X2$	0.0177	-0.1909	-0.0420
$X3$	0.2164	-0.6134	-0.8541
$X4$	-0.2804	-0.1388	-0.0177
$X5$	0.6236	-0.0574	-04320

Table 4: Standardized data sample set.

Years	GDP_t	$X5_{t-1}$	$X10_{t-2}$	$X10_{t-3}$	$X11_{t-1}$	$X12_{t-1}$
2015	0.07451	0.38538	0.03734	0.09768	0.03570	0.06221
2016	0.10137	0.09749	0.14584	0.03734	0.07451	0.11126
2017	0.12705	-0.07452	0.24929	0.14584	0.10137	0.10273
2018	0.14211	-0.03902	0.30461	0.24929	0.12705	0.10204
2019	0.18479	0.43677	0.18634	0.3046 1	0.14211	0.13500
2020	0.14026	0.74904	0.09017	0.18634	0.18479	0.18060

output variable, then this indicates that the time series problem may be unpredictable.

3.1.2. Moving Average Model (MA).

$$y_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}. \quad (16)$$

Among them, y_t represents the current value, μ is the constant term, and ε_t is the error term.

3.1.3. Autoregressive Moving Average Model (ARMA).

$$y_t = \mu + \sum_{i=1}^{p} \gamma_i y_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}. \quad (17)$$

The ARMA model is a combination of the AR model and the MA model.

3.1.4. Moving Average Autoregressive Model (ARIMA). The principle of the ARIMA (p, d, q) model is as follows: the lag value $\sum_{i=1}^{p} \gamma_i y_{t-i}$, the random error value ε_t, and the lag value $\sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$of the random error value are performed; the model is established by regression. Its expression can be written as follows:

Table 5: Comparison table of several regression model error rates (MSEs).

Experimental sample	Linear regression	Support vector regression	Nearest neighbor return	Random forest regression
CPI	0.0183	0.0116	0.0019	0.0110
GDP	0.0063	0.0130	0.0145	0.0150

$$Y_t = \mu + \sum_{i=1}^{p} \gamma_i y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t. \quad (18)$$

3.2. Economic Forecast Indicators. The use of neural network models for economic forecasting is the process of using the nonlinear function trained with sample data to obtain the predicted value. However, due to the large differences between different economic indicators, the correlation is strong or weak. Economic indicators include consumer price index and gross domestic product. Therefore, it is particularly important to select appropriate impact indicators as the input of the neural network in the model prediction. These are the type of neural network (such as MLP and CNN), input data, computing power (determined by hardware and software capabilities), learning rate, and mapped output function. However, most of the index selections in the existing literature are based on the researcher's experience and are highly subjective. This paper analyzes the importance of the characteristics of the 39 indicators collected and uses scientific methods to scientifically and objectively screen the indicators. In the scientific method, the correlation coefficient method, regression analysis method, principal component analysis method, factor analysis method, correspondence analysis method, cluster analysis method, etc., can all be used as screening methods in scientific and objective screening indicators. Whether the predictive index we choose during modeling is reasonable has a lot to do with the accuracy of our predictive results. Data association view can help us understand the relationship between variables. The main variables are traditional gray LPSVR, unbiased gray LPSVR, moving average method improved gray LPSVR, and combined gray LPSVR. Evaluating the generalization performance of the model is an important part of the experimental project. To select an appropriate evaluation standard to evaluate the model reasonably, we need to select reasonable indicators as the performance measurement of the model. The economic forecasting problem is a regression problem, and its forecast results and true values are continuous. Each sample will get two corresponding probability values, one is the probability that the sample is a positive sample, and the other is the probability that the sample is a negative sample. The probability that each sample is a positive sample is taken out and sorted, and then, a threshold is selected, and the samples larger than this threshold are judged as positive samples, and the samples less than the threshold are judged as negative samples, and then, two values can be obtained.

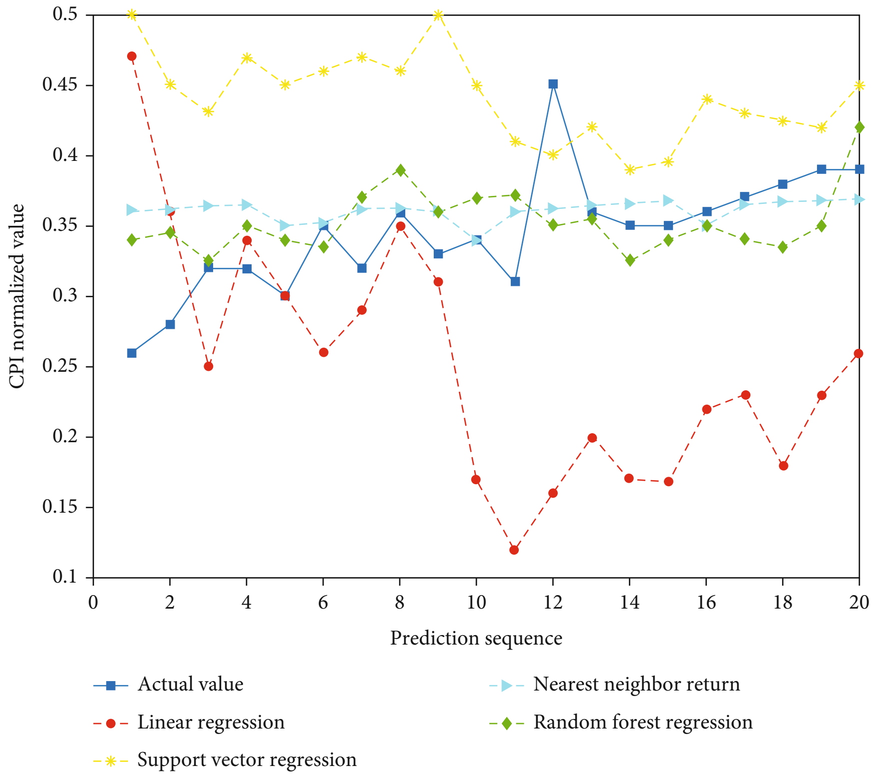

Figure 4: CPE of various regression models in the CPI sample data set.

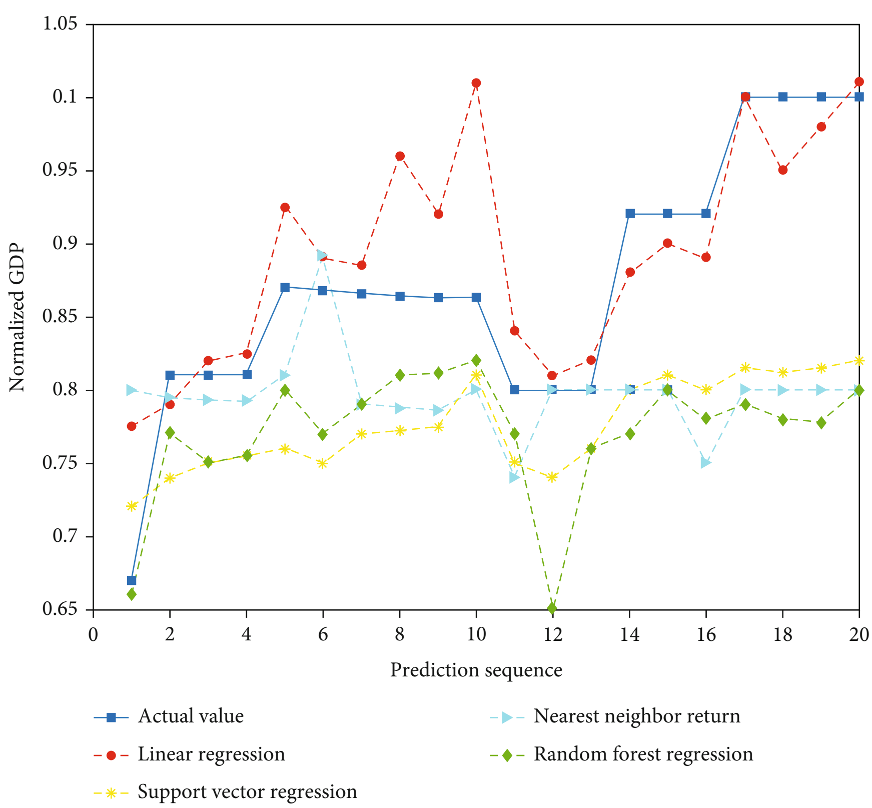

Figure 5: CPE of various regression models in the GDP sample data set.

Table 6: ε-SVR model prediction comparison results.

Years	Predictive value	Actual value	Relative error
2015	1602.98	1603.16	0.01%
2016	1779.92	1765.68	0.81%
2017	1989.56	1990.01	0.02%
2018	2261.37	2272.82	0.50%
2019	2512.59	2692.81	6.69%
2020	3067.01	3070.49	0.11%

3.3. Experimental Design. Because economic forecasts are highly time-sensitive, in most cases, we need to make economic forecasts without knowing the specific values of the influencing factors to solve this kind of problem. The experiment in this section introduces the gray model. At the same time, although the traditional gray model is suitable for small sample prediction and has strong versatility, it also has defects such as being easily affected by random factors and poor long-term prediction effect. The unbiased gray model can well solve the problem of the limited prediction length of the traditional gray model; the improved gray model based on the moving average method can well eliminate the influence of random factors. The gray prediction model is a prediction method that establishes a mathematical model and makes predictions through a small amount of incomplete information. It is an effective tool for dealing with small-sample prediction problems. For small-sample prediction problems, regression and neural networks are not effective. Therefore, the experiment in this section establishes a combined gray model to predict influencing factor value prediction. These four models are LPSVR model, LSPM model, ν-SVR model, and ε-SVR model. The error rates of the economic forecast data set under the four models are shown in Table 1.

The comparison chart of CPI prediction results under multiple combination models is shown in Figure 3.

4. Forecast Results and Model Analysis

4.1. Support Vector Machine Regression Prediction Process. The general process of using SVM for forecasting is as follows: select appropriate indicators to create an indicator system, and select historical data for continuous time series samples based on the characteristics of the research. Standardize the sample data, and create a training sample set and a test sample set. Select the appropriate SVR type, kernel form, and related parameter values.

4.1.1. Data Sample Selection and Preprocessing. According to the established indicator system, the collected data are shown in Table 2, and the data sources are "Guilin City Statistical Yearbook" and "China Statistical Yearbook."

4.1.2. The Composition of Sample Data. Regional economic forecasting is a kind of time series forecasting. Predict the future economic growth level based on the known historical information. Therefore, the data sample should be the historical information of each indicator in the indicator system and the corresponding economic aggregate level.

According to the established initial indicator system, the sum of the training samples is the selected initial fiscal statistics of Guilin City from 2015 to 2020. The data format is (GDP_t, X_{t-1}), GDP_t comes from GDP in year t, and $X_{t-1} = (X1_{(t-1)}, X1_{(t-2)}, X1_{(t-3)}, X2_{(t-1)}, X2_{(t-2)}, X2_{(t-3)} \cdots, Xm_{(t-1)}, Xm_{(t-2)}, Xm_{(t-3)})$ is a vector composed of variables of each influencing factor from year t-1 to year $t-3$, that is, the input from year $t-1$ to year $t-3$ is used to describe the output in year t.

As a result, the model index soared from the first 13 to 39. This not only significantly increases the complexity of the model, but the amount of data in the sample makes it difficult to support appropriate statistical significance. Therefore, it is necessary to reduce the existing indicators before processing data and building models. Correlation analysis is used to classify the indicators, and the correlation between the growth rate of each indicator and the GDP growth rate is shown in Table 3.

4.1.3. Data Preprocessing. The purpose of data inspection is to check the accuracy, completeness, and consistency of the statistical classification of data. Data integrity and accuracy are critical. In addition, the consistency of the statistical caliber is also very important. If the data of some samples are taken from other calipers, it will affect the relationship between the indicators of standardization. Due to the different dimensions and ranges of data values, the values of different indicators may vary greatly. When solving problems, large indicators often have a great influence on the results, while low-value and high-value factors may have little influence. To avoid this, you often need to normalize the data and convert all parameters to the same range. Table 4 shows the standard data sample set.

4.1.4. Division of Sample Set. In order to predict SVM more accurately, the original data sample set should be split into a training sample set and a test sample set. The training sample set trains the SVM, builds the model, and checks the sample set to verify the accuracy of the model's prediction. In this article, we decompose the data into total training samples and test samples every two years and select the lowest and highest total GDP growth training samples to avoid the "expansion" problem to the greatest extent.

4.2. Forecast Effect. Based on economic forecast data, this article uses the sklearn library to build several common regression models for performance comparison. And draw the prediction result and the true value into a line graph, to show the prediction effect more intuitively. The comparison of several regression model error rates (MSEs) is shown in Table 5.

Figure 4 shows the comparison of the prediction effects (CPE) of multiple regression models on the CPI sample data set.

Figure 5 shows the CPE of multiple regression models on the GDP sample data set.

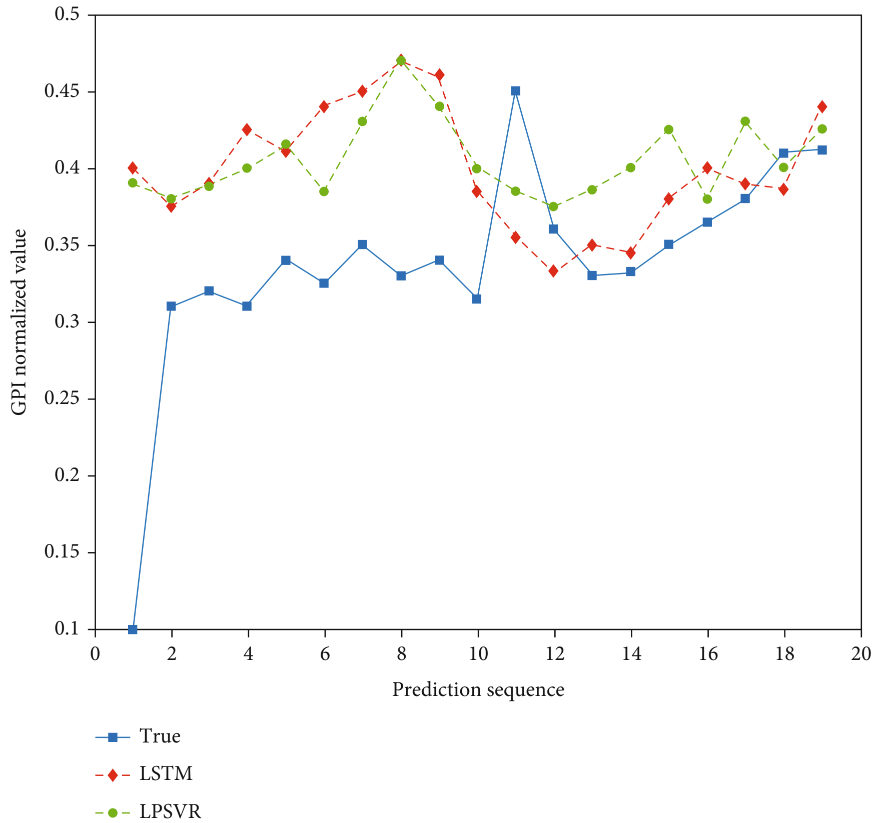

Figure 6: Comparison of GPI predicted values between LPSVR model and LSPM model.

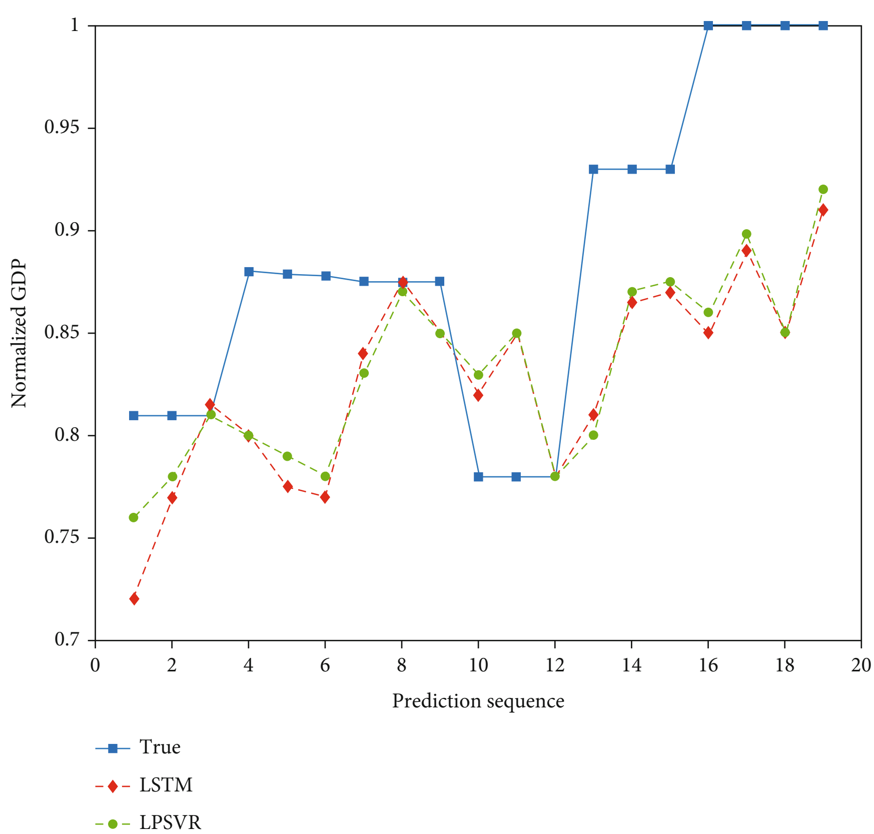

Figure 7: Comparison of GDP predicted values between LPSVR model and LSPM model.

Table 7: ε-SVR model prediction and comparison results.

Years	Predictive value	Actual value	Relative error
2015	1603.10	1603.16	0.00%
2016	1780.23	1765.68	0.82%
2017	1989.94	1990.01	0.00%
2018	2261. 84	2272.82	0.48%
2019	2512.85	2692.81	6.68%
2020	3068.26	3070.49	0.07%

Table 8: Comparison of Guilin's GDP forecast in 2021.

Years	Actual value	ε-SVR predictive value	ε-SVR error	ν-SVR predictive value	ν-SVR error
2021	3486.20	3365.31	3.47%	3365.80	3.45%

SVM modeling is performed with the selected kernel function parameters, SVM parameters, and corresponding training sample sets, and the consistency and independence tests are performed, respectively. The comparison between the predicted results and the actual values is shown in Table 6.

It can be seen from Table 6 that the ε-SVR model has a very good fitting effect for the economic growth forecast of Guilin, with an average error of only 1.58%, especially the forecast error from 2015 to 2018 is less than 1%, and the forecast error is relatively large. The major years have occurred in the years when there are major changes in policy factors. However, due to the limited selection of data samples in the model, the changes in economic growth due to policy changes have not been fully expressed, resulting in a certain delay. However, it just reflects the influence of qualitative factors (such as policy changes) on modeling. The comparison between the prediction results of the support vector machine and the neural network is shown in Figure 6.

Figure 7 shows the comparison of the GDP predicted value between the LPSVR model and the LSPM model.

ε-SVR and ν-SVR are two commonly used algorithms for support vector regression, and -SVRSVR uses ε when constructing support vector machines. In sensitive loss function, and ν-SVR is an improvement of -SVR, and the parameter ν is introduced instead of the parameter ε. In the following content of this section, we use the ν-SVR model to make predictions and compare them with the prediction results of ε-SVR. The process and steps of using ν-SVR for regional economic forecasting modeling are the same as ε-SVR. Under the same sample data set and indicator system, the same training sample set and prediction sample set are used, and the parameters are carried out under the same kernel function conditions. The relatively good prediction result and its training error obtained at the end are shown in Table 7.

In Table 7, we can see that the training and testing errors of the two SVR types are very close, the maximum prediction difference is 0.05%, and the minimum is almost the same. It can be seen from Figures 6 and 7 that the average relative error of the ν-SVR model is 1.57%, which is smaller than the 1.58% average relative error of the -SVR model and the relative error of the ν-SVR model. However, the results of the two SVR applications in this study show that they perform very well in terms of learning and promotion and can be used as the final model, and further data testing will discuss which is better.

It can be seen from Table 8 that the predicted values of the two SVR types are very close, which are 3363.31 and 3365.80, respectively. The data published in the prospectus have 3.47% and 3.45% errors, respectively. The main reason for the big error is that the strategy elements have changed significantly during the SVM training process, but due to the limited data selection, the model may not be able to reflect the entire process. Therefore, you can choose to continuously increase the number of training samples in the subsequent learning and training process to minimize the impact of these emergencies on the model prediction.

5. Conclusions

Regional economic development is an open, dynamic, and complex system, including economic, political, social, natural resources, environment, science and technology, and other influencing factors. The relationship between these factors is complex and ultimately reflects the economic growth of the region. Regional economic development presents highly nonlinear characteristics, and it is difficult to obtain satisfactory results with traditional predictive analysis methods. Through the analysis of Guilin's annual statistical data, the LPSV forecast model will be used for empirical research. Starting from the factors affecting regional economic development, based on broad economic theory, combined with resource allocation theory, construct a regional economic development evaluation index system. The three-year retrospective calculation of various metric data is the initial data sample set. The metrics are sorted through correlation analysis, and standardized values are calculated based on the growth rate of standard metric data. The model optimization process uses a grid search method for kernel operation and supports machine parameter selection to simultaneously check the relationship between parameters. Finally, the parameter set with the highest prediction accuracy is selected to construct the support carrier machine. The prediction results of the two support regression models show that the support engine is very effective in predicting the level of economic growth in Guilin. In view of the time and space complexity problems that may be caused by quadratic programming, linear programming support vector regression algorithm is introduced; in view of the credibility of prediction results, the concept of prediction trust is introduced. The linear programming support vector regression model with predictive confidence is applied to the regional economic development prediction, which not only improves the prediction accuracy but also improves the credibility of the prediction results.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors state that this article has no conflict of interest.

References

[1] S. H. Chen, R. C. Feiock, and J. Y. Hsieh, “Regional partnerships and metropolitan economic development,” *Journal of Urban Affairs*, vol. 38, no. 2, pp. 196–213, 2016.

[2] H. Kasseeah, “Investigating the impact of entrepreneurship on economic development: a regional analysis,” *Journal of Small Business & Enterprise Development*, vol. 23, no. 3, pp. 896–916, 2016.

[3] J. Zhao, X. Li, Y. Liu, X. Wang, and C. Zhou, “Ionospheric foF2 disturbance forecast using neural network improved by a genetic algorithm,” *Advances in Space Research*, vol. 63, no. 12, pp. 4003–4014, 2019.

[4] L. Lei, Z. O. U. Haibo, and H. E. Zhiming, “Algorithm of vertical profiles of radar echoes between any two points based on webpage and its application,” *Meteorological and Environmental Research*, vol. 11, no. 1, pp. 38–43, 2020.

[5] Z. Yin, S. Tieyuan, and Y. Fang, “Test study on flood forecast by merging multi precipitation data,” *Meteorological and Environmental Research*, vol. 9, no. 2, pp. 54–61, 2018.

[6] A. Battisti, O. C. Acevedo, F. D. Costa, F. S. Puhales, V. Anabor, and G. A. Degrazia, “Evaluation of nocturnal temperature forecasts provided by the weather research and forecast model for different stability regimes and terrain characteristics,” *Boundary-Layer Meteorology*, vol. 162, no. 3, pp. 523–546, 2017.

[7] L. Weihong, W. Lei, and C. Yebin, “Spatialtemporal forecast research of property crime under the driven of urban traffic factors,” *Multimedia Tools & Applications*, vol. 75, no. 24, pp. 17669–17687, 2016.

[8] B. N. Porfiryev and A. S. Tulupov, “Environmental hazard assessment and forecast of economic damage from industrial accidents,” *Studies on Russian Economic Development*, vol. 28, no. 6, pp. 600–607, 2017.

[9] N. Arai, “Evaluating the efficiency of the FOMC's new economic projections,” *Journal of Money Credit & Banking*, vol. 48, no. 5, pp. 1019–1049, 2016.

[10] M. Guckes, “2017 precision machined products industry economic forecast,” *Production Machining*, vol. 17, no. 3, pp. 28–31, 2017.

[11] A. A. Shirov, M. S. Gusev, and A. R. Sayapova, “Scientific and technological dimensions of the macrostructural forecast,” *Studies on Russian Economic Development*, vol. 27, no. 6, pp. 611–620, 2016.

[12] B. Kacar, J. Curic, and S. Ikic, “Local economic development in theories of regional economies and rural studies,” *Ekonomika poljoprivrede*, vol. 63, no. 1, pp. 231–246, 2016.

[13] H. Chen, K. Dong, F. Wang, and E. C. Ayamba, “The spatial effect of tourism economic development on regional ecological efficiency,” *Environmental Science and Pollution Research*, vol. 27, no. 10, pp. 1–18, 2020.

[14] C. Lenzi, “The pursuit of economic development,” *Papers in Regional Science*, vol. 98, no. 4, pp. 1855–1858, 2019.

[15] A. Cm, A. Ga, A. Ak, and C. Malesios, “Fostering regional development in eastern Macedonia and Thrace, Greece, through road transport projects,” *Economic Analysis and Policy*, vol. 65, no. 3, pp. 56–67, 2020.

[16] X. Tang and G. Wang, “Design and analysis of e-commerce and modern logistics for regional economic integration in wireless networks,” *EURASIP Journal on Wireless Communications and Networking*, vol. 2020, no. 1, 15 pages, 2020.

[17] S. Krapohl, “Games regional actors play: dependency, regionalism, and integration theory for the Global South,” *Journal of International Relations and Development*, vol. 23, no. 4, pp. 840–870, 2020.

[18] B. Ywa, L. A. Jian, L. A. Rong, X. Suo, and E. Lu, “Precipitation forecast of the Wujiang River Basin based on artificial bee colony algorithm and backpropagation neural network,” *Alexandria Engineering Journal*, vol. 59, no. 3, pp. 1473–1483, 2020.

[19] A. Ketabi and M. H. Fini, “Adaptive underfrequency load shedding using particle swarm optimization algorithm,” *Journal of Applied Research & Technology*, vol. 15, no. 1, pp. 54–60, 2017.

[20] I. V. Small, “Wandering money: valuating and mediating postwar remittances in Vietnam,” *TRaNS: Trans-Regional and -National Studies of southeast Asia*, vol. 9, no. 1, pp. 31–43, 2021.

[21] Y. Jiajia, H. Yuqi, and G. Qian, “Soil erosion and regional industrial upgrading in the Yangtze River surrounding area based on ecological evaluation,” *Arabian Journal of Geosciences*, vol. 14, no. 11, pp. 1–20, 2021.

[22] Z. Zeng, “The impact of vegetation change and climate in coastal cities on public sports: the impact of urban heat island,” *Arabian Journal of Geosciences*, vol. 14, no. 10, pp. 1–18, 2021.

[23] M. V. Zotova, V. A. Kolosov, A. A. Gritsenko, A. B. Sebentsov, and M. S. Karpenko, “Territorial gradients of socioeconomic development of Russia's borderland,” *Regional Research of Russia*, vol. 9, no. 1, pp. 32–43, 2019.

[24] V. V. Berlepsch, A. Rodriguez-Pose, and N. Lee, “A woman's touch? Female migration and economic development in the United States,” *Regional Studies*, vol. 53, no. 1, pp. 131–145, 2019.

[25] R. Capello, “Regional development theories and formalised economic approaches: an evolving relationship,” *Italian Economic Journal*, vol. 5, no. 1, pp. 1–16, 2019.

[26] A. Y. Trotskovskii and Y. A. Perekarenkova, “Altai Krai under conditions of economic instability: key trends and features of development,” *Regional Research of Russia*, vol. 9, no. 1, pp. 44–52, 2019.